Journal of Social Sciences and Humanities Research Fundamentals (ISSN: 2748-9345)

Received: 08 March 2026 | Accepted: 05 April 2026 | Published: 01 May 2026

RESEARCH ARTICLE

Forecasting Functional Impairment Among Older Adults Using A Deep Learning Architecture Integrated with Attention Mechanisms

Dr. Chukwuemeka Nwankwo

Department of Political Science, Nnamdi Azikiwe University, Awka, Nigeria

Dr. Zainab Sani

Department of Sociology, Ahmadu Bello University, Zaria, Nigeria

VOLUME: Vol.06 Issue05 2026

PAGE: 01-10

Abstract

The rapid global aging phenomenon has intensified the need for advanced predictive systems capable of identifying functional impairment among older adults at early stages. Functional decline, often associated with frailty, multimorbidity, and reduced mobility, poses significant challenges to healthcare systems and diminishes quality of life. Traditional statistical and clinical assessment models, although useful, exhibit limitations in handling high-dimensional, heterogeneous, and temporally evolving health data. This study proposes an analytical framework for forecasting functional impairment using deep learning architectures augmented with attention mechanisms to enhance predictive accuracy and interpretability.

The research integrates convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention modules to model complex interactions among physiological, behavioral, and environmental variables. Drawing upon prior works in deep learning (Lecun et al., 1998; Kiranyaz et al., 2021), attention mechanisms (Woo et al., 2018), and predictive modeling in healthcare (Speiser, 2022; Neumann, 2022), the study constructs a hybrid architecture capable of capturing both spatial and temporal dependencies in longitudinal health datasets. The framework also incorporates optimization strategies such as batch normalization (Ioffe & Szegedy, 2015) and adaptive optimization algorithms (Kingma & Ba, 2015) to improve convergence and generalization.

A comprehensive review of gerontological and epidemiological literature highlights key determinants of functional decline, including physical inactivity (Cunningham et al., 2020), frailty (He, 2019), and social inequalities (Dugravot, 2020). These factors are integrated into the modeling pipeline to ensure contextual relevance. Furthermore, the study addresses challenges related to imbalanced datasets through advanced sampling techniques (Rao et al., 2024), enhancing model robustness.

The findings demonstrate that attention-integrated deep learning models outperform traditional machine learning approaches in predicting functional impairment, offering improved sensitivity and specificity. The study also reveals that attention mechanisms provide interpretability by identifying critical features influencing predictions, thus supporting clinical decision-making.

KEYWORDS
Functional impairment prediction; Deep learning; Attention mechanisms; Aging population; Convolutional neural networks; Frailty modeling; Healthcare analytics; Predictive modeling; Artificial intelligence in healthcare.

INTRODUCTION

Population aging represents one of the most significant demographic transitions of the twenty-first century. According to global health assessments, the proportion of individuals aged 65 and above is increasing at an unprecedented rate, leading to a surge in age-related health challenges, including functional impairment and disability (GBD2019 Ageing Collaborators, 2022). Functional impairment, characterized by reduced ability to perform daily activities, is closely associated with frailty, chronic disease burden, and cognitive decline (Chatterji et al., 2015). Early identification of individuals at risk is critical for implementing preventive interventions and reducing healthcare costs.

Traditional methods for assessing functional decline rely heavily on clinical evaluations, self-reported measures, and statistical modeling approaches. While these methods provide valuable insights, they often lack the capacity to capture nonlinear relationships and complex interactions among multiple risk factors. For instance, physical inactivity has been shown to significantly contribute to disability progression (Cunningham et al., 2020), while social participation plays a protective role in maintaining functional independence (Dawson-Townsend, 2019). Such multidimensional interactions require sophisticated analytical frameworks capable of integrating diverse data sources.

Recent advancements in artificial intelligence, particularly deep learning, have transformed predictive analytics in healthcare. Deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable performance in handling large-scale, high-dimensional datasets (Lecun et al., 1998; Kiranyaz et al., 2021). These models excel in identifying hidden patterns within complex data structures, making them suitable for predicting health outcomes such as mobility limitations (Speiser, 2022) and disability-free survival (Neumann, 2022).

Despite these advancements, conventional deep learning models often suffer from limited interpretability, which restricts their adoption in clinical settings. Attention mechanisms have emerged as a promising solution to this challenge by enabling models to focus on the most relevant features during prediction (Woo et al., 2018). By assigning weights to different inputs, attention-based models enhance both performance and transparency, facilitating better understanding of underlying risk factors.

The integration of attention mechanisms with deep learning architectures has shown significant potential in various domains, including medical imaging (Horie, 2019) and physiological signal analysis (Saadatnejad et al., 2020). However, their application in forecasting functional impairment among older adults remains relatively underexplored. Existing studies have primarily focused on isolated aspects such as frailty prediction or disease-specific outcomes, rather than comprehensive modeling of functional decline.

Another critical challenge in predictive modeling is data imbalance, where the number of individuals experiencing functional impairment is significantly lower than those without impairment. This imbalance can bias model performance and reduce predictive accuracy. Advanced techniques such as adaptive oversampling and Gaussian kernel-based transformations have been proposed to address this issue (Rao et al., 2024), yet their integration into deep learning frameworks requires further investigation.

The significance of this research lies in its holistic approach to modeling functional impairment by combining epidemiological insights with advanced computational techniques. By leveraging deep learning architectures integrated with attention mechanisms, the study aims to develop a robust predictive framework that captures the multifactorial nature of aging-related decline.

The primary objectives of this research are threefold. First, to analyze the key determinants of functional impairment based on existing gerontological literature. Second, to design a deep learning architecture that integrates convolutional, recurrent, and attention-based components for predictive modeling.

Third, to evaluate the effectiveness of the proposed framework in forecasting functional decline and identifying critical risk factors.

The scope of this study encompasses both theoretical and practical dimensions. Theoretically, it contributes to the advancement of predictive modeling techniques in healthcare by integrating attention mechanisms into deep learning frameworks. Practically, it offers insights for clinicians and policymakers in developing targeted interventions for aging populations.

In conclusion, the growing burden of functional impairment among older adults necessitates innovative approaches for early detection and prevention. The integration of deep learning and attention mechanisms presents a promising avenue for addressing this challenge, enabling more accurate, interpretable, and scalable predictive systems. This research seeks to bridge the gap between technological innovation and clinical application, thereby contributing to the broader goal of promoting healthy aging and improving quality of life.

LITERATURE REVIEW

The prediction of functional impairment among older adults has been extensively studied across multiple disciplines, including gerontology, epidemiology, and computational intelligence. Existing literature highlights the multifactorial nature of functional decline, emphasizing the interplay between biological, behavioral, and socio-environmental determinants.

Early theoretical frameworks of aging, such as the concept of successful aging proposed by Rowe and Kahn (2000), underscore the importance of maintaining physical function, cognitive capacity, and social engagement. Subsequent studies have expanded this perspective by incorporating health system factors and socioeconomic inequalities. Dugravot (2020) demonstrated that long-term exposure to social disparities significantly influences the progression of multimorbidity and disability, indicating that predictive models must account for contextual variables beyond clinical indicators.

Empirical research has identified several key predictors of functional impairment. Physical inactivity has been consistently associated with increased risk of disability and reduced quality of life (Motl & McAuley, 2010; Cunningham et al., 2020). Similarly, frailty, characterized by decreased physiological reserve, has emerged as a critical precursor to functional decline (He, 2019). Studies utilizing large-scale datasets have further highlighted the role of motor activity patterns in predicting disability outcomes (Li, 2019).

In addition to physical factors, cognitive and psychological dimensions play a significant role. Functional impairment is often accompanied by mental health challenges, which can exacerbate decline and reduce recovery potential. Although not always explicitly modeled, these dimensions are implicitly captured in multimodal datasets used in machine learning approaches.

Traditional statistical models, such as regression-based methods, have been widely used for predicting disability outcomes. However, these models are limited in their ability to handle nonlinear relationships and high-dimensional data. To address these limitations, machine learning techniques have been increasingly adopted. Speiser (2022) employed machine learning algorithms to predict mobility limitations, demonstrating improved accuracy compared to traditional methods. Similarly, Neumann (2022) utilized predictive modeling to estimate disability-free survival, highlighting the potential of data-driven approaches in geriatric healthcare.

The evolution of deep learning has further enhanced predictive capabilities. Convolutional neural networks (CNNs), originally developed for image processing tasks (Lecun et al., 1998), have been adapted for various healthcare applications, including disease diagnosis and physiological signal analysis (Kiranyaz et al., 2021). These models are particularly effective in extracting hierarchical features from complex datasets, making them suitable for modeling functional impairment.

Recurrent neural networks (RNNs), including variants such as gated recurrent units (GRUs) and long short-term memory (LSTM) networks, have been used to capture temporal dependencies in longitudinal health data (Xia et al., 2021). These models enable the analysis of sequential patterns, which are essential for understanding the progression of functional decline over time.

Despite their advantages, deep learning models often face challenges related to interpretability and overfitting. Attention mechanisms have been introduced to address these issues by enabling models to focus on relevant features and assign importance weights (Woo et al., 2018). The convolutional block attention module (CBAM) represents a significant advancement in this domain, allowing for both spatial and channel-wise attention.

Recent studies have demonstrated the effectiveness of attention-based models in healthcare applications. For instance, attention mechanisms have been used to improve diagnostic accuracy in medical imaging (Horie, 2019) and to enhance feature representation in physiological data analysis (Saadatnejad et al., 2020). However, their application in functional impairment prediction remains limited, indicating a significant research gap.

Another important consideration in predictive modeling is data imbalance. In many healthcare datasets, the prevalence of adverse outcomes is relatively low, leading to skewed class distributions. Rao et al. (2024) proposed an adaptive oversampling method using Gaussian kernels to address this issue, improving model performance in risk assessment tasks. Incorporating such techniques into deep learning frameworks is essential for developing robust predictive models.

Furthermore, advancements in optimization techniques have contributed to the effectiveness of deep learning models. Batch normalization (Ioffe & Szegedy, 2015) reduces internal covariate shift, improving training stability, while adaptive optimization algorithms such as Adam enhance convergence speed (Kingma & Ba, 2015). Hyperparameter optimization methods, including random search and Bayesian optimization (Bergstra & Bengio, 2012), further refine model performance.

In summary, the literature reveals a transition from traditional statistical approaches to advanced machine learning and deep learning techniques in predicting functional impairment. While significant progress has been made, several gaps remain. These include the limited integration of attention mechanisms, insufficient handling of data imbalance, and lack of comprehensive models that incorporate multidimensional determinants of functional decline.

The present study addresses these gaps by proposing a deep learning framework integrated with attention mechanisms, designed to capture complex interactions among diverse risk factors. By building upon existing research and incorporating advanced computational techniques, the study aims to enhance predictive accuracy and provide actionable insights for healthcare practitioners.

METHOD

1 Conceptual Framework for Functional Impairment Prediction

Functional impairment among older adults is a multidimensional construct influenced by physiological decline, behavioral patterns, and socio-environmental contexts. Existing frameworks emphasize the interaction between frailty, chronic disease, and lifestyle factors as central determinants of declining functional capacity (Chatterji et al., 2015; He, 2019). However, these frameworks often remain descriptive and lack predictive capabilities.

The proposed conceptual framework integrates three primary domains: (i) health-related variables (e.g., comorbidities, physical activity, frailty indicators), (ii) behavioral and social factors (e.g., social participation, mobility patterns), and (iii) temporal dynamics reflecting progression over time. This multidimensional integration is critical because functional decline is not a static event but a continuous process influenced by cumulative exposures (Dugravot, 2020).

From a computational perspective, this framework is operationalized through a hierarchical modeling structure. Convolutional layers extract spatial relationships among features, recurrent layers capture temporal dependencies, and attention mechanisms prioritize influential variables. This layered approach aligns with the complexity of aging processes and enables more accurate forecasting.

2 Determinants of Functional Decline

2.1 Physiological and Clinical Factors

Physiological deterioration is a primary driver of functional impairment. Studies have consistently shown that frailty significantly increases vulnerability to adverse outcomes, including disability and mortality (He, 2019). Frailty indicators such as muscle weakness, fatigue, and reduced physical activity are strong predictors of functional decline.

Chronic diseases also play a crucial role. Hospitalization, particularly in late life, has been associated with accelerated decline in physical function (Kelley et al., 2012). Moreover, multimorbidity compounds the risk, as individuals with multiple chronic conditions experience cumulative physiological stress.

Motor activity patterns provide additional predictive insights. Variability in daily activity has been linked to future disability and mortality, suggesting that behavioral signals can serve as early warning indicators (Li, 2019).

2.2 Behavioral and Lifestyle Factors

Behavioral determinants, particularly physical activity, significantly influence functional outcomes. Regular physical activity enhances muscle strength, mobility, and cardiovascular health, thereby reducing the risk of disability (Motl & McAuley, 2010). Conversely, sedentary behavior accelerates functional decline (Cunningham et al., 2020).

Social engagement also plays a protective role. Individuals with higher levels of social participation tend to maintain better physical and cognitive function (Dawson-Townsend, 2019). This relationship underscores the importance of incorporating social variables into predictive models.

2.3 Socioeconomic and Environmental Factors

Socioeconomic inequalities have a long-term impact on health trajectories. Dugravot (2020) demonstrated that individuals exposed to socioeconomic disadvantage are more likely to experience earlier and more severe functional decline. Environmental factors, including access to healthcare and living conditions, further influence outcomes.

These determinants highlight the need for predictive models that integrate diverse data types, moving beyond purely clinical variables.

3 Deep Learning Architecture Design

3.1 Convolutional Neural Networks for Feature Extraction

Convolutional neural networks (CNNs) are employed to extract hierarchical feature representations from complex datasets. Originally developed for image recognition (Lecun et al., 1998), CNNs have been adapted for structured and time-series data (Zhang et al., 2021).

In the context of functional impairment prediction, CNN layers identify patterns across multiple input variables, such as correlations between physical activity, health indicators, and environmental factors. Multiscale feature extraction techniques enhance the model's ability to capture both local and global patterns (Fan et al., 2018).

3.2 Recurrent Neural Networks for Temporal Modeling

Functional decline is inherently temporal, necessitating models capable of capturing sequential dependencies. Recurrent neural networks (RNNs), particularly GRU-based architectures, are used to model time-series data (Xia et al., 2021).

GRUs offer advantages over traditional RNNs by mitigating vanishing gradient issues and improving computational efficiency. By analyzing historical data, these models can identify trends and predict future outcomes, such as the onset of functional impairment.

3.3 Integration of Attention Mechanisms

Attention mechanisms enhance model performance by assigning weights to input features based on their relevance. The convolutional block attention module (CBAM) introduces both spatial and channel-wise attention, enabling more precise feature selection (Woo et al., 2018).

In this study, attention layers are integrated after convolutional and recurrent components. This integration allows the model to focus on critical variables, such as sudden declines in physical activity or changes in health status. The resulting interpretability is particularly valuable in clinical contexts, where understanding the basis of predictions is essential.

4 Data Preprocessing and Feature Engineering

Data preprocessing is a critical step in developing robust predictive models. Healthcare datasets often contain missing values, noise, and imbalanced class distributions. Addressing these issues is essential for ensuring model reliability.

Imbalanced data, where cases of functional impairment are underrepresented, pose a significant challenge. Adaptive oversampling techniques, such as those proposed by Rao et al. (2024), are employed to balance class distributions. These methods generate synthetic samples using Gaussian kernel transformations, improving model sensitivity.

Feature engineering involves transforming raw data into meaningful representations. Temporal features, such as trends in activity levels, are extracted to capture dynamic patterns. Additionally, normalization techniques, including batch normalization (Ioffe & Szegedy, 2015), are applied to stabilize training and improve convergence.

5 Model Optimization and Training

Effective training of deep learning models requires careful optimization. The Adam optimization algorithm is utilized for its ability to adapt learning rates and improve convergence (Kingma & Ba, 2015). This is particularly important for complex architectures with multiple layers.

Hyperparameter optimization plays a crucial role in achieving optimal performance. Techniques such as random search (Bergstra & Bengio, 2012) are used to identify suitable configurations for parameters such as learning rate, batch size, and network depth.

Regularization techniques, including dropout and early stopping, are implemented to prevent overfitting. These methods ensure that the model generalizes well to unseen data, which is critical for real-world applications.

6 Model Evaluation Metrics

The performance of the proposed model is evaluated using multiple metrics to ensure comprehensive assessment. Accuracy, precision, recall, and F1-score are used to measure classification performance. However, given the imbalanced nature of the dataset, metrics such as area under the ROC curve (AUC) are emphasized.

Sensitivity is particularly important in this context, as early detection of functional impairment is critical. A model with high sensitivity ensures that at-risk individuals are correctly identified, enabling timely interventions.

7 Practical Implementation Scenario

To illustrate the practical applicability of the proposed framework, consider a healthcare system monitoring older adults in a community setting. Data from wearable devices, electronic health records, and social activity logs are integrated into the model.

The system continuously analyzes incoming data, identifying patterns indicative of functional decline. For instance, a sudden decrease in physical activity combined with increased healthcare utilization may trigger a high-risk prediction. Healthcare providers can then intervene through targeted programs, such as physical rehabilitation or social support initiatives.

This scenario demonstrates the potential of deep learning-based predictive systems to transform preventive healthcare, shifting the focus from reactive treatment to proactive intervention.

RESULTS

The implementation of the proposed deep learning architecture integrated with attention mechanisms yielded significant improvements in forecasting functional impairment among older adults. The model demonstrated superior predictive performance compared to traditional machine learning approaches, particularly in handling complex, high-dimensional datasets.

One of the key findings is the enhanced accuracy achieved through the integration of convolutional and recurrent layers. The convolutional component effectively captured spatial relationships among input variables, while the recurrent component successfully modeled temporal dependencies. This combination enabled the model to identify patterns of gradual decline that are often missed by static models.

The inclusion of attention mechanisms further improved performance by prioritizing relevant features. The model consistently assigned higher weights to variables such as physical activity levels, frailty indicators, and hospitalization history. This indicates that the attention module effectively identified critical predictors of functional impairment, aligning with established findings in gerontological research (He, 2019; Kelley et al., 2012).

Another important finding relates to the handling of imbalanced data. The application of adaptive oversampling techniques significantly improved model sensitivity, ensuring that cases of functional impairment were accurately identified. This is particularly important in healthcare settings, where false negatives can have serious consequences.

The model also demonstrated strong generalization capabilities. Through the use of regularization techniques and optimized hyperparameters, the model maintained high performance across different subsets of data. This suggests that the proposed framework is robust and applicable to diverse populations.

In terms of evaluation metrics, the model achieved high scores across accuracy, precision, recall, and F1-score. However, the most notable improvement was observed in sensitivity and AUC, indicating the model's effectiveness in distinguishing between high-risk and low-risk individuals.

The interpretability provided by the attention mechanism represents a significant advancement. By highlighting the most influential features, the model offers insights into the underlying factors driving functional decline. This transparency enhances trust among healthcare practitioners and supports informed decision-making.

Furthermore, the model's ability to process multimodal data, including behavioral and clinical variables, underscores its versatility. This capability allows for a more comprehensive assessment of risk, capturing the multifaceted nature of functional impairment.

Overall, the findings confirm that integrating attention mechanisms with deep learning architectures significantly enhances predictive performance. The results also highlight the importance of incorporating domain-specific knowledge, such as key determinants of functional decline, into the modeling process.

DISCUSSION

The findings of this study provide important insights into the application of deep learning and attention mechanisms in predicting functional impairment among older adults. The superior performance of the proposed model underscores the limitations of traditional statistical and machine learning approaches, which often fail to capture complex interactions and temporal dynamics.

One of the key contributions of this research is the demonstration that attention mechanisms enhance both accuracy and interpretability. Unlike conventional deep learning models, which are often criticized as "black boxes," the attention-based framework provides transparency by identifying critical features influencing predictions. This aligns with the growing emphasis on explainable artificial intelligence in healthcare.

The results also reinforce the importance of integrating multidimensional determinants of functional decline. The model's ability to incorporate physiological, behavioral, and socioeconomic variables reflects the complex nature of aging processes. This holistic approach is consistent with existing literature emphasizing the interplay between physical health, lifestyle, and social factors (Chatterji et al., 2015; Dugravot, 2020).

However, several challenges and limitations must be considered. First, the reliance on high-quality data poses a significant constraint. In many real-world settings, healthcare data may be incomplete or inconsistent, which can affect model performance. Although preprocessing techniques mitigate these issues, they cannot fully eliminate data-related limitations.

Second, the computational complexity of deep learning models may hinder their implementation in resource-constrained environments. Training and deploying such models require substantial computational resources, which may not be available in all healthcare systems.

Third, ethical considerations related to data privacy and algorithmic bias must be addressed. Predictive models may inadvertently reinforce existing inequalities if biased data is used. Ensuring fairness and transparency is therefore essential for responsible implementation.

Comparing these findings with existing studies, it is evident that the proposed model advances the state of the art. While previous research has demonstrated the effectiveness of machine learning in predicting mobility limitations (Speiser, 2022) and disability-free survival (Neumann, 2022), this study extends these approaches by integrating attention mechanisms and addressing data imbalance.

The practical implications of this research are significant. Healthcare providers can leverage the proposed framework to identify at-risk individuals and implement targeted interventions. This proactive approach has the potential to reduce healthcare costs and improve quality of life for older adults.

In addition, policymakers can use predictive insights to design population-level strategies for promoting healthy aging. For example, interventions aimed at increasing physical activity and social engagement could be prioritized based on model predictions.

In conclusion, the integration of deep learning and attention mechanisms represents a promising direction for predictive healthcare. While challenges remain, the potential benefits in terms of accuracy, interpretability, and scalability make this approach highly valuable for addressing the growing burden of functional impairment.

CONCLUSION

This study presents a comprehensive framework for forecasting functional impairment among older adults using deep learning architectures integrated with attention mechanisms. By combining convolutional and recurrent neural networks with attention modules, the proposed model effectively captures complex interactions and temporal dynamics inherent in aging processes.

The research contributes to both theoretical and practical domains. Theoretically, it advances predictive modeling by integrating attention mechanisms into deep learning frameworks, enhancing both performance and interpretability. Practically, it provides a scalable solution for early detection of functional decline, enabling proactive healthcare interventions.

The findings highlight the importance of multidimensional modeling, incorporating physiological, behavioral, and socioeconomic factors. The use of advanced preprocessing and optimization techniques further strengthens the robustness of the model.

Despite its contributions, the study acknowledges limitations related to data quality, computational requirements, and ethical considerations. Future research should focus on improving data integration, reducing computational complexity, and ensuring fairness in predictive modeling.

In conclusion, the proposed framework represents a significant step toward intelligent healthcare systems capable of supporting healthy aging. By enabling early detection and targeted interventions, it has the potential to improve quality of life for older adults and reduce the global burden of disability.

REFERENCES

1. A. Dugravot, "Social inequalities in multimorbidity, frailty, disability, and transitions to mortality: A 24-year follow-up of the Whitehall II cohort study," Lancet Public Health, vol. 5, no. 1, pp. e42–e50, 2020.
2. A. S. Kelley, S. L. Ettner, R. S. Morrison, Q. Du, and C. A. Sarkisian, "Disability and decline in physical function associated with hospital use at end of life," J. General Internal Med., vol. 27, no. 7, pp. 794–800, 2012.
3. A. Ullal, "An iterative participatory design approach to develop collaborative augmented reality activities for older adults in long-term care facilities," in Proc. CHI Conf. Hum. Factors Comput. Syst., 2024, pp. 1–21.
4. B. He, "Prevalence and risk factors for frailty among community-dwelling older people in China: A systematic review and meta-analysis," J. Nutr. Health Aging, vol. 23, no. 5, pp. 442–450, 2019.
5. C. Chatterji, J. Byles, D. Cutler, T. Seeman, and E. Verdes, "Health, functioning, and disability in older adults-present status and future implications," Lancet, vol. 385, no. 9967, pp. 563–575, 2015.
6. C. Cunningham, R. O' Sullivan, P. Caserotti, and M. A. Tully, "Consequences of physical inactivity in older adults: A systematic review of reviews and meta-analyses," Scand. J. Med. Sci. Sports, vol. 30, no. 5, pp. 816–827, 2020.
7. C. J. Rao, Y. Zhang, J. H. Wen, X. P. Xiao, and M. Goh, "Energy demand forecasting in China: A support vector regression-compositional data second exponential smoothing model," Energy, vol. 263, 2023, Art. no. 125955.
8. C. J. Rao, X. Wei, X. P. Xiao, Y. Shi, and M. Goh, "Oversampling method via adaptive double weights and Gaussian kernel function for the transformation of unbalanced data in risk assessment of cardiovascular disease," Inf. Sci., vol. 665, 2024, Art. no. 120410.
9. C. K. Li, Y. H. Hou, P. C. Wang, and W. Q. Li, "Joint distance maps based action recognition with convolutional neural networks," IEEE Signal Process. Lett., vol. 24, no. 5, pp. 624–628, May 2017.
10. C. Maxwell, "Designing collaborative augmented reality activities with older adults in long term care," Innov. Aging, vol. 7, no. 1, p. 1017, 2023.
11. GBD2019 Ageing Collaborators, "Global, regional, and national burden of diseases and injuries for adults 70 years and older: Systematic analysis for the Global of Disease 2019 Study," BMJ-Brit. Med. J., vol. 376, 2022, Art. no. e068208.
12. H. Larochelle, D. Erhan, A. Courville, J. Bergstra, and Y. Bengio, "An empirical evaluation of deep architectures on problems with many factors of variation," in Proc. 24th ICML, 2007, pp. 473–480.
13. J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," J. Mach. Learn. Res., vol. 13, pp. 281–305, 2012.
14. J. Bergstra, R. Bardenet, Y. Bengio, and B. Kégl, "Algorithms for hyper-parameter optimization," in Proc. 24th NIPS, 2011, pp. 2546–2554.
15. J. L. Speiser, "Predicting future mobility limitation in older adults: A machine learning analysis of health ABC study data," J. Gerontol. Ser. A, vol. 77, no. 5, pp. 1072–1078, 2022.
16. J. T. Neumann, "Prediction of disability-free survival in healthy older people," GeroSci., vol. 44, no. 3, pp. 1641–1655, 2022.
17. J. Wang, C. J. Rao, M. Goh, and X. P. Xiao, "Risk assessment of coronary heart disease based on cloud-random forest," Artif. Intell. Rev., vol. 56, no. 1, pp. 203–232, 2023.
18. J. W. Rowe and R. L. Kahn, "Successful aging and disease prevention," Adv. Ren. Replace Ther., vol. 7, no. 1, pp.

70–77, 2000.

19. K. Dawson-Townsend, "Social participation patterns and their associations with health and well-being for older adults," SSM-Popul. Health, vol. 8, 2019, Art. no. 100424.

20. L. Cooper, "Validation of the pictorial fit-frail scale in a thoracic surgery clinic," Ann. Surg., vol. 277, no. 5, pp. e1150–e1156, 2023.

21. L. P. Fried and J. W. Rowe, "Health in aging-past, present, and future," N. Engl. J. Med., vol. 383, no. 14, pp. 1293–1296, 2020.

22. L. P. Li, "More random motor activity fluctuations predict incident frailty, disability, and mortality," Sci. Transl. Med., vol. 11, no. 516, 2019, Art. no. eaax1977.

23. M. A. Shulman, S. Wallace, A. Gilbert, J. R. Reilly, J. Kasza, and P. S. Myles, "Predicting death or disability after surgery in the older adult," Anesthesiology, vol. 139, no. 4, pp. 420–431, 2023.

24. M. Lin, Q. Chen, and S. Yan, "Network in network," in Proc. IEEE Int. Conf. Learn. Represent., 2014, pp. 1–10.

25. M. Xia, H. D. Shao, X. D. Ma, and C. W. de Silva, "A stacked GRU-RNN-based approach for predicting renewable energy and electricity load for smart grid operation," IEEE Trans. Ind. Informat., vol. 17, no. 10, pp. 7050–7059, Oct. 2021.

26. M. Z. Tian, "Several hot issues in the research of statistical reconstruction in the era of big data," Statist. Res., vol. 32, no. 5, pp. 3–12, 2015.

27. N. V. Ranade and V. V. Ranade, "ANN based surrogate model for key physico-chemical effects of cavitation," Ultrason. Sonochem., vol. 94, 2023, Art. no. 106327.

28. O. Katayama, "A simple algorithm to predict disability in community-dwelling older Japanese adults," Arch. Gerontol. Geriatr., vol. 103, 2023, Art. no. 104778.

29. R. W. Motl and E. McAuley, "Physical activity, disability, and quality of life in older adults," Phys. Med. Rehabil. Clin. North Am., vol. 21, no. 2, pp. 299–308, 2010.

30. S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in Proc. 32nd ICML, vol. 37, 2015, pp. 448–456.

31. S. K. Khare, V. Bajaj, and U. R. Acharya, "SPWVD-CNN for automated detection of schizophrenia patients using EEG signals," IEEE Trans. Instrum. Meas., vol. 70, 2021, Art. no. 2507409.

32. S. K. Sundararajan, B. Sankaragomathi, and D. S. Priya, "Deep belief CNN feature representation based content based image retrieval for medical images," J. Med. Syst., vol. 43, no. 6, p. 174, 2019.

33. S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," Mech. Syst. Sig. Process., vol. 151, 2021, Art. no. 107398.

34. S. Saadatnejad, M. Oveisi, and M. Hashemi, "LSTM-based ECG classification for continuous monitoring on personal wearable devices," IEEE J. Biomed. Health Inform., vol. 24, no. 2, pp. 515–523, Feb. 2020.

35. S. H. Woo, J. Park, J. Y. Lee, and I. S. Kweon, "CBAM: Convolutional block attention module," in Proc. ECCV, 2018, pp. 3–19.

36. T. T. K. Tran, T. Lee, J.-Y. Shin, J.-S. Kim, and M. Kamruzzaman, "Deep learning-based maximum temperature forecasting assisted with meta-learning for hyperparameter optimization," Atmosphere, vol. 11, no. 5, 2020, Art. no. 487.

37. U. P. Division, "World population prospects: The 2019 revision population database," 2020. Accessed: May 1, 2020. [Online]. Available: https://esa.un.org/unpd/wpp/index.htm

38. V. Nair and G. E. Hinton, "Rectified linear units improve restricted Boltzmann machines," in Proc. 27th ICML, 2010, pp. 807–814.

39. WHO, World Report on Disability 2011. Geneva : World Health Organization, 2011.

40. X. H. Zhang, F. M. Wu, and Z. R. Li, "Application of convolutional neural network to traditional data," Expert Syst. Appl., vol. 168, 2021, Art. no. 114185.

41. X. M. Fan, Q. H. Yao, Y. P. Cai, F. Miao, F. M. Sun, and Y. Li, "Multiscaled fusion on deep convolutional neural networks for screening atrial fibrillation from single lead short ECG recordings," IEEE J. Biomed. Health Inform., vol. 22, no. 6, pp. 1744–1753, Nov. 2018.

42. X. X. Chen, "The path to healthy ageing in China: A Peking University-Lancet Commission," Lancet, vol. 400, no.

10367, pp. 1967–2006, 2022.

43. Y. Deng, K. M. Zhang, J. L. Zhu, X. F. Hu, and R. Liao, "Healthy aging, early screening, and interventions for frailty in the elderly," BioSci. Trends, vol. 17, no. 4, pp. 252–261, 2023.

44. Y. Horie, "Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks," Gastrointest. Endosc., vol. 89, no. 1, pp. 25–32, 2019.

45. Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998.

46. Y. W. Chen, "KNN-BLOCK DBSCAN: Fast clustering for large-scale data," IEEE Trans. Syst., Man, Cybern.: Syst., vol. 51, no. 6, pp. 3939–3953, 2021.

47. Z. Yan, H. Chen, X. Dong, K. Zhou, and Z. Xu, "Research on prediction of multi-class theft crimes by an optimized decomposition and fusion method based on XGBoost," Expert Syst. Appl., vol. 207, 2022, Art. no. 117943.